GROUND TARGET CLASSIFICATION FOR AIRBORNE BISTATIC RADAR

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Abstract

Surveillance, be it in real time or offline, is one of the most strategic actions in any military operation. In this the use of synthetic aperture radar (SAR) images has proved extremely useful due to the all weather capability. But with the amount of data that modern SAR can output, automated detection and classification facilities have become inevitable. With the present resurgence in interest in bistatic radars, and some unique advantages of the same, futuristic usage of bistatic radars should increase. We are in the beginning of our project aiming at development of algorithms for bistatic SAR image classification of ground-based targets. In the present correspondence the state of the art classification approaches for SAR images of terrestrial targets has been analysed. And the potentiality of the bistatic radar for SAR classification has been examined.

Keywords: SAR, ATR, classification, bistatic radar

Introduction

Modern fighter aircrafts are becoming ever more complex and powerful in their abilities and performance, and output a huge amount of data about a wide spectrum of parameters to the operator. Hence automated systems are on an ever higher demand for defence systems, as has been reviewed by Bhanu (1). SAR automated target recognition (ATR) systems are a great value addition if SAR mapping is already integrated in the system. SAR ATR for ground based targets is also important in battle field surveillance. The popularity of SAR ATR comes due to the all weather imaging ability of SAR system. Also, with higher resolution, SAR images have become very close to optical images as far as clarity is concerned. SAR systems use longer wavelength, and hence can often be used for foliage penetration (FOPEN) to detect hidden targets. SAR images are built from the raw electro magnetic (EM) scattered energy, and so they contain information about the EM properties of the targets, and hence can sometimes prove more important than simple optical images in target recognition.

Bistatic radars have shown excellent possibilities for opportunistic operations (as reviewed by Hawkins (3)), counter jamming abilities, counter stealth abilities, clutter tuning, and in getting more complete information about the target (as described by Willis (2)). Hence irrespective of the present day technical complexities involved, bistatic SAR ATR is a trend for tomorrow.

Target Classification for Monostatic Radar

Most of the reports in the open literature about SAT ATR till now have been on monostatic radars. Some of the major approaches towards ATR have been:

Approaches by the MIT-Lincoln Lab

US-defence advanced research project

agency (DARPA) funded semi-automated IMINT (image intelligence) processing (SAIP) project has been a forerunner in research into SAR ATR. In this the major role in ATR has been played throughout by the Novak et al (4,5,6) team from the MIT-Lincoln Lab. In all the approaches, due to the exhaustive amount of data available, mean squares estimation (MSE) algorithm has been used for classification purpose. In 1995, DARPA and AFRL initiated a program called the moving and stationary target acquisition recognition (MSTAR). Under this program, a huge amount of data was collected using X-band, HH-polarised SAR sensors for a large number of military vehicles. Since then, the MSTAR data base has been a major source for testing and validation of most of the ATR algorithms in literature. In their basic approach towards SAR ATR, three steps are followed.

- Prescreening: Selecting the regions of interest (ROI) from the SAR image.
- Discrimination: Processing the ROI to avoid any false alarm, and generating the features.
- Classification: Using the features to classify the target.

They have also dealt with fully polarimetric data, super resolution SAR images, and various combination of features in the target to evaluate the performance (4,5,6).

While most of the standard SAR ATR research has been done by the Lincoln Lab. group, their approaches have mostly been cantered around the huge data from the MSTAR exercise. But SAR image can vary in a sensitive manner depending upon the SAR system used. And there has been no *sensitivity analysis*, of the algorithm or features used.

Likelihood test Algorithms

There has been a number of approaches using a likelihood test algorithms on the MSTAR data base for classification purposes, using different models for the SAR image. In the major work done by Prof.O'Sullivan et al (7,8), three types of models, conditioned on the target type and orientation, have been assumed and applied to the MSTAR data base. The models considered are:

Conditionally Gaussian Model: The SAR image pixels are modelled as conditionally *Gaussian* random variable.

Log-magnitude Model: In this model, the *complex valued* pixels of the SAR image are assumed to be independent and follow *Lognormal* distribution.

Quarter Power Model: The image pixels can also be modelled as random variables with *Gamma* distribution.

The models were compared with respect to the computing load experienced and depending on the performance in the recognition task. The conditional Gaussian model was shown to be marginally the best choice of the three (8).

Approaches in exploiting polarimetric information

Most of the major ATR approaches have used uni-polar SAR data. If used at all, the fully polarimetric SAR data has been exploited mostly for better image formation. Novak *et al*, have used the fully polarimetric data using the polarimetric whitening filter (PWF) processing, for speckle filtering and getting better quality SAR images (4). The different polarisation information has been used in a limited sense by them in *P*olarimetric *F*eature determination to give some information about odd or even bouncing of the scattered rays (4,5). However in monostatic radar polarimetric data has been proved to have much more particular information about the target physical features and aspects, by Huynen (9), than has been exploited by Novak et al (4,5).

In another work, decomposition of the scattering matrix into three components has been proposed by Krogager (10). This has been done with the assumption that scattering from any surface can be approximated to that from a sphere or diplane or helix.

$[S] = k_s[S]_{sphere} + e^{j\phi_n}(k_d[S]_{diplane} + k_h[S]_{hellix}),$

where $e^{j\phi_n}$, is the normalised phase angle. Using monostatic-SAR imaging an imaginary scene made up of discrete scatterers of particular well defined geometrical shapes was generated. It was shown how mapping different polarisation returns, and also measurement of the above coefficients, give information about certain types of scatterers. Hence applied properly, information can be extracted about the geometry of the target.

Polarimetric return has also been shown theoretically to provide better information as regard to classification of SAR images is concerned, by Sadjadi (11). In the referred works, Fisher distance in a predefined feature space (for SAR image of a few military vehicles) has been compared for different sets of tilt and ellipticity angle in both transmission and reception systems. And it was shown how for particular combination of transmission and reception polarimetric state (coined as the *Optimal Polarimetric combination*), the features are most distinct (gain of around 2.5dB above any random combination of polarimetric states).

Complex-valued data

A SAR image is formed from the complex valued data obtained from the receiver. But mostly, the image is formed using the absolute magnitude and classification steps are taken after the image-formation procedure. There has been some ATR approaches (7,8) using complex valued data. In one of the limited analysis, it has been shown by Sadjadi (12) that taking complex data may significantly increase possibility of classification performance. The work is limited in a few aspects, like:

- only two targets have been considered.
- only one feature has been considered for comparing.
- actual classification exercise has not been performed to show the real performance.

But still, this limited work, does show the scope for fully complex-data for classification purpose.

Exploiting scattering center principle

SAR images of man-made objects often can be approximated as coming from distinct scattering centers. There has been some research on extracting these scattering centers from the SAR image and using them in turn, for classification and recognition exercises. Because:

- By considering the scattering centers, the computing load is heavily reduced from dealing with a huge amount of pixels, to that of dealing with only a small number of scattering centers.
- Scattering centers' response in SAR are dependant on the scattering phenomena experienced by the radiation. Hence it depends on the physical features of the target, which information in turn may prove more useful in ATR operation.

The approach in using scattering centers for ATR can be consolidated under two major steps:

Extracting the Scattering Centers from SAR Image: Bhalla et al (13), have proposed an algorithm for extracting the position of the scattering centers from the SAR image. The algorithm is an iterative algorithm, which assumes the brightest available pixel in the SAR image to correspond to the position of a scattering center. In each iteration, it determines the brightest pixel and tries to separate that pixel (scattering center), and its effect from the whole image. This is achieved by the following operation:

$$(residual\_image)_{n+1} = (residual\_image)_n - [A_n h(x - x_n, y - y_n)]$$

where A_n is the brightest point's strength in the nth iteration , and $h(x - x_n, y - y_n)$ is the point spread function for the SAR Image. Mostly a two dimensional (2-D) *sinc* function has been shown to be appropriate.

Extracting Information from the Scattering Centers: As discussed by Chiang et al (14), the return from a scattering center can be modeled, with each scattering center can be associated with a set of seven parameters $(A_n, x_n, y_n, \alpha_n, \gamma_n, L_n, \phi_n)$. Here return from *n*th scattering center is modeled with return strength A_n, frequency dependence of a_n, spatial position at x_n, y_n, length of L_n, damped-exponential factor of g_n(for localised scattering center), and orientation angle of f_n. □ is the azimuth angle of the radar to the scene center. In some of their works, Moses et al (14,15) have used the scattering-center principle for SAR image classification. They have considered the more detailed model as put above and also two simpler approximate models, the damped exponential model and the undamped exponential model. They have used a least squares estimator (LSE) for estimating the parameters of the scattering centers, and have reported encouraging results. In a later work, Moses et al (15) have utilised this principle for SAR ATR, based on the MSTAR database. In that they have only used a Bayesian classifier for the purpose, and have also used the complex-valued SAR image to estimate the (scattering center) model parameters. Results have been comparable to those by Novak et al.

ANN and SVM approaches

There have also been some approaches towards SAR ATR using nonlinear networks like artificial neural network(ANN), support vector machines(SVM), radial basis functions network(RBFN) etc. In one of the correspondences, Gross (16) describe an ANN based approach to detect moving targets. In that it has been claimed that if high range resolution (HRR) data is handled directly for recognition, before framing any image out of that, then it can help in the detection of moving targets as well. To generate the HRR set of vectors, inverse Fourier transform (IFT) was taken of the SAR images, and then non-coherent integration was carried out to generate desired amount of range profiles. These HRR data (angle vs. range) has been used to train the ANN. Although these results have not been very encouraging, still it has been claimed that in actual real life flight it might be of use.

In another approach, Zhao and Bao (17) have used RBFN for recognising targets. In this the HRR profiles have also been used, both in training and in the operation phase. They have shown how RBFN results in determining the decision boundary is more effective than the traditional (Parzen window) kernel classifiers.

Zhao and Principe (18) have used SVM for SAR ATR. In this approach dealing with MSTAR data set, the SAR image has been directly used for the purpose. They have investigated a wide combination of networks for classification. empirical risk minimisation (ERM) rule applied through delta rule with weight decay network, structural risk minimisation (SRM) applied through SVM and optimal hyperplane networks have been considered. SVM has been concluded as the best among all the topologies considered.

Subaperture and HMM approaches

In addition to the above methods, there has been a few very novel ways of approaching SAR ATR problem.

In an interesting approach, Kim et al (19) give a novel idea for SAR image segmentation and analysis. In this, the full aperture is divided on a tree-basis into a set of sub-apertures. As the speckle and scattering center response change according to the aspect angle, the sub-apertures are claimed to give different features of the image. The feature vector for each pixel is derived from all the subapertures, as a vector xÎ$\boldsymbol{R}^d$. The phase information (complex nature of SAR data) has also been

taken into consideration. Some results have been shown with verification done on the MSTAR data base. Results have been compared with those from wavelet and template-matching methods, showing the proposed method as comparable and in some aspects better than the other two.
Runkle et al (20), have tried to use the principle of hidden Markov model (HMM) in SAR ATR. The HRR profile for the same target varies as per the aspect angle (19). Markov Chain rule can be used to describe the consecutive HRRs. As the target type and its pose are the factors determining the final observation and they in themselves are not known, the final model is claimed to be a HMM. MSTAR data base has been used in the validation process and the HRR profiles have been back-generated from the target SAR images. Though results reported are comparable to those from Novak et al, the processing involved is too demanding as far as computing resource is concerned. The use of 120 states in the HMM (as done in the correspondence) in itself seems formidable. But still the logic of using HMM is promising.

Why Bistatic for Classification?

Bistatic Radars have been slowly regaining their popularity. But still there exists very little open literature on bistatic radar signal processing in general and bistatic SAR processing in particular.
In a limited study of practical images from some exemplar simple bodies, Gupta et al (21) have shown that for higher order diffraction bistatic images vary markedly from monostatic images. In another recent study Hsieh and Fung (22) have proposed scattering models for bistatic multiple scattering phenomena. Germond et al (23) have given studies and closed formula for calculating polarimetric variables for bistatic radars. But there has been almost no report in the open literature about bistatic radar imaging applied for ATR purpose. Some limited initial studies by Nashashibi and Ulaby (24) show that bistatic radars are more effective in detecting targets in clutters.
As a preliminary simulation approach, a synthetic target was simulated for generating its bistatic RCS pattern for various bistatic angles.

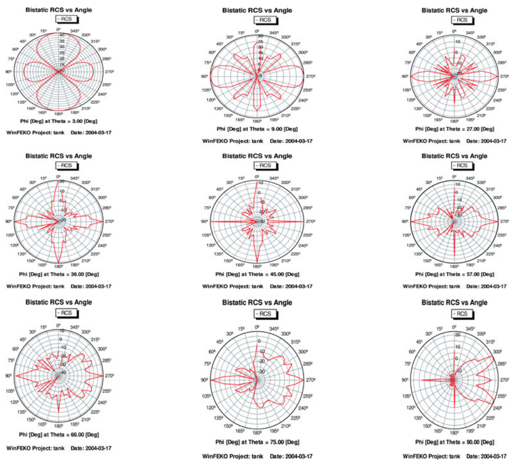

Fig.1 *Bistatic RCS pattern for various bistatic angles*

As can be seen, the variation in bistatic angles, drastically change the RCS pattern, showing that bistatic views do give a more complete and exhaustive information about the target. Hence the utility of bistatic radar in target classification does seem highly promising.

Conclusion and Perspectives

Due to the unique strategic advantages offered by the bistatic arrangement, and possible upper hand in target feature extraction, bistatic imaging and classification, SAR ATR is supposed to be an extremely important tool in military environment.
The current project aims at attacking the problem of SAR ATR from two perspectives, which are proposed to be novel. First, ATR problem is to be analysed for bistatic system. Second, the problem would be tried to be addressed by applying as much as possible *a priory* information about the EM interaction taking place.

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References

1. Bhanu B.1993, IEEE AES Magazine,10, 15-22
2. Willis, N., 1995, "Bistatic Radar", Technology Service Corporation, USA.
3. Hawkins 1997, IEE Radar Conference, 318-322.
4. Novak L.,Burl M, and Irving W, 1993 IEEE Trans. AES,29,1, 234-243.
5. Novak L.,Halversen S.,Owirka G., and Hiett M., 1997 IEEE Trans. AES, 33,1, 102-115.
6. Novak L., 2000, IEEE Radar Conf., 836-843.
7. O'Sullivan J., DeVore M., Kedia v., and Miller M., 2001, IEEE Trans. AES,37,1, 91-106.
8. DeVore M., and O'Sullivan J., 2002,IEEE Trans. AES,38,2, 632-648.
9. Huynen J., 1991, IEE ICAP Conf., 257-261.
10. Krogager E.,1991, Telesystem Conf., 77-82.
11. Sadjadi F.,1998,RADARCON, 293-298.
12. Sadjadi F.,2002, IGARSS Conf., 2504-2506.
13. Bhalla R., and Liang H.,1996, IEEE Trans. AP,44,11, 1445-1453.
14. Chiang H., Moses R., and Potter L., 2000, IEEE Trans. Information Theory,46,5, 1842-1854.
15. Potter L., and Moses R., 1997, IEEE Trans. Image Processing, 6,1, 79-91.
16. Gross D, 1999, Signals,Systems and Computers 33rd Conf., 1235-1239.
17. Zhao Q., and Bao Z., 1996,Neural Network,9,4, 709-720.
18. Zhao Q., and Principe J., 2001, IEEE Trans. AES,37,2, 643-654.
19. Kim A., Fisher J., Willsky A., and Viola P., 1999, SPIE Conf. on Algorithms for SAR Imagery,VI, 332-342.
20. Liao X., Runkle P., and Carin L., 2002, IEEE Trans. AES, 38,4, 1230-1242.
21. Burkholder R, Gupta I, and Johnson J, 2003, IEEE AP Magazine,45,3, 41-50.
22. Hsieh C, and Fung A, 2003, IEE AP Proceedings, 214-218.
23. Germond A, Pottier, and Saillard J, 1997, Radar 97 Conf., 833-837.
24. Nashashibi A, and Ulaby F, 2003, IEEE APS Int. Symp., 424-427.